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Abstract

This paper explores dynamic conditional and unconditional causality relation between intraday return and order imbalance on extraordinary events. We examine the dynamics in NASDAQ speculative top losers. In this study, we introduce a multiple hypotheses nested causality method for identifying the dynamic conditional and unconditional causality relation between intraday returns and order imbalances. The volume-stratified results suggest order imbalance be a better return predictor in small trading volume quartile. The order imbalance-based trading strategies are useful from 11:30 A.M. to 2 P.M. than in other time regimes.

Keywords: causality, top loser, order imbalance, information asymmetry, multiple hypotheses testing method.
JEL Classification: G12, G14.

Introduction

There are many papers focusing on daily relation between trading volume and return dynamics. Although volume is an important linkage between stock return and trading activity (Karpoff, 1987), volumes convey less information about trading than order imbalances do (Chan & Fong, 2000). A large order imbalance has a great impact on price movement because it signals private information (Kyle, 1985), exerts pressure on market maker's inventory, and prompt a change in quotes (Stoll, 1978). Chordia and Subrahmanyam (2004) find that imbalance-based trading strategies yield statistically significant returns. Moreover, Andrade, Chang and Seasholes (2008) indicate that non-informational imbalances generate predictable reversals in stock returns under a multi-asset equilibrium model. Although the literature suggests a strong association between stock returns and order imbalances, a discussion of dynamic causality relation between intraday return and order imbalance is rare. Brown, Walsh and Yuen (1997) find bi-directional causality between returns and order imbalances, but not beyond a single day. To know whether information asymmetry has a significant influence on return-order imbalance relation, we need a measure of information asymmetry. Since information asymmetry is not directly observable, a suitable proxy is necessary. Lo and MacKinlay (1990) and Llorente, Michaely, Sarr, and Wang (2002) use firm size to measure information asymmetry. They argue that firms with larger size have a lower degree of information asymmetry. The larger the firm is, the more regulations, debt holders, equity holders and analysts it involves. Therefore, the extent of transparency in larger firms is higher than that in smaller firms. Easley, Kiefer, O'Hara and Paperman (1996) argue that private information is more important for illiquid stocks. They also document that illiquid stocks have a higher probability of informed trading. Most studies explore the relation between return and order imbalance on extraordinary events. For example, Blume, MacKinlay and Terker (1989) examine order imbalances around the October 1987 crash, while Lee (1992) analyzes order imbalances around earnings announcements. The above events provide an ideal laboratory in which to examine the relation between price formation and order imbalances. Llorente et al. (2002) recognize that there are two types of trades: hedging and speculative trade. They find that the relatively higher importance of speculative trade is associated with higher information asymmetry. Therefore, we put emphasis on examining the relation between intraday return and order imbalance in NASDAQ speculative top losers. Besides, Cornell and Sirri (1992) find insider trading often takes place from noon to 2 P.M. in a specific illegal insider trading.

We employ a systematic multiple-hypothesis testing method, namely a nested causality, to investigate dynamic conditional and unconditional causality relation between intraday returns and order imbalances. Unlike traditional pair-wise hypothesis testing, this multiple hypotheses testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis.

In this paper, we find that the volume-stratified results suggest that order imbalance is a return predictor in small trading volume quartile. The order imbalance-based trading strategies are useful from 11:30 A.M. to 2 P.M. than in other time regimes because the percentage of firms exhibiting a unidirectional relationship from order imbalance to return is the highest in this period.

The rest of this paper is organized as follows. Section 1 describes data and methodology. In section 2, we discuss empirical results. The last section concludes.

1. Data and methodology

Owing to the high frequency of financial data, empirical studies based upon daily data usually fail to catch information contained in intraday market movements. Therefore, we use the 90-second cumulative transaction data[1], including order time, order imbalances and prices. A selection of NASDAQ speculative top losers is in our sample. Our sample period is from Oct. 19, 2004 to Dec. 17, 2004. In this period, we get 50 samples. In the 90 second trading interval, there are 260 trading intervals within a trading day. These data are available on the Island-ECN website[2], which offers U.S. broker-dealers access to one of the most robust liquidity pools in NASDAQ equities.

Due to the following main advantages, there are more investors trading on ECN (Electronic Communication Network). Investors reduce market interposition cost and prevent from middlemen's prying eyes. Moreover, ECN provides extended transactions before and after market. Barclay, Hendershott and Mccormick (2003) find ECN offers the advantages of anonymity and speed of execution, which attract informed traders. Trades are more likely to occur on ECN when information asymmetry is greater. There is more private information revealed through ECN trades than through market maker trades.

Panel A of Table 1 presents the descriptive statistics of buyer (seller)-initiated trades and order imbalances[3] of NASDAQ top losers from Oct. 19, 2004 to Dec. 17, 2004. We find that the mean of OINUM is -1.72 percent of total trades while the mean of OISHA is -2.30 percent of total shares. The mean of OIDOL is -0.08 percent of total dollar volumes. It implies that investors' intention to sell stocks is greater than that to buy stocks in NASDAQ top losers. The means and standard deviations of buy and sell orders per trade are presented in Panel B of Table 1. The mean of OISHA (OIDOL) per buy trade is 211.78 (2675.55) and that of per sell trade is -218.68(-2643.20), indicating that the share is higher and the stock price is lower when investors sell stocks than when they buy stocks.

Panel C exhibits the intraday trading behaviors during the event day. We divide the whole day into three sub-periods: period 1 (9:30 A.M.-11:30 A.M.), period 2 (11:30 A.M. – 2:00 P.M.) and period 3 (2:00 P.M. – 4:00 P.M.). The number, share and dollar volume of order imbalance are positive in period 1, while those are negative in period 2, indicating that the buy orders still surpass sell orders in the morning. Nonetheless, the situation is changed from 11:30 A.M. to 2 P.M. The stock prices of top losers show an upward tendency in the morning and decline from 11:30 A.M. to 2 P.M. The number of trading volume is high in period 1 and low in period 2. The results are the same for shares and dollar value of trading volume. We find a U-shaped intraday trading volume pattern[4].

Table 1. Descriptive statistics of buy/sell trades and order imbalances

Panel A. Numbers of trades and orders

	Mean	Maximum	Minimum
Number of buy trades	956	2633	93
Number of sell trades	989	2225	160
OINUM/Total trades (%)	-1.72	8.39	-26.48
Number of buy shares	189474	440806	16791
Number of sell shares	198393	491730	24484
OISHA/Total trades (%)	-2.30	-5.46	-18.63
Number of buy dollars	2393938	13233727	29382
Number of sell dollars	2397974	11860668	50048
OIDOL/Total orders (%)	-0.08	5.47	-26.02

Panel B. Means and standard deviations of order per trade

	Mean	S.D.	Maximum	Minimum
OISHA per buy trade	211.78	185.37	999.00	1.00
OISHA per sell trade	-218.68	191.23	-999.00	-1.00
OIDOL per buy trade	2675.77	3249.82	40365.00	3.98
OIDOL per sell trade	-2643.20	3247.09	-40167.00	-2.75

[1] Lee, Fok and Liu (2001) use 6-minute intervals with each interval containing nearly 12 trades on average. Ekinci (2004) constructs 5-min intervals for an intraday analysis of stocks with 27.3 trades per interval on average. For our sample period in only one day, we shorten the time interval. In addition, for NASDAQ dealers are required to report trades within 90 seconds, we use 90-second intervals to catch the intraday seasonality.

[2] The Island-ECN website is "http://www.island.com". We would sign trades using Lee and Ready (1991) algorithm if we use the NYSE Trades and Automated Quotations (TAQ) databases. Unlike TAQ databases, the "Time and Sales" database provided by Island-ECN has indicated the sign of trades.

[3] For each stock, we define the order imbalance (volume) as follows:. OINUM (VOLNUM) is the number of buyer-initiated trades minus (plus) that of seller-initiated trades, OISHA (VOLSHA) is the share of buyer-initiated trades minus (plus) that of seller-initiated trades and OIDOL (VOLDOL) is the dollar volume of buyer-initiated trades, minus (plus) that of seller-initiated trades.

[4] Trading is highest at the beginning and at the end of the day.

Panel C. Means of order imbalances and trading volumes in different time regimes

Time of day	OINUM	OISHA	OIDOL	VOLNUM	VOLSHA	VOLDOL
Period 1	30.42	4233.46	204587.31	765.42	150990.70	2826364.52
Period 2	-2.30	-5305.79	-60363.40	282.37	53137.06	933258.12
Period 3	13.83	-815.67	-49504.89	530.42	99855.14	1794141.80

In order to examine dynamic conditional and unconditional causality relation between returns and order imbalances, we introduce a VAR model by Chen and Wu (1999). We define four relationships between two random variables, x_1 and x_2, in terms of constraints on the conditional variances of $x_{1(T+1)}$ and $x_{2(T+1)}$ based on various available information sets, where $\underset{\sim}{x_i}=(x_{i1}, x_{i2}, ..., x_{iT})$, i=1, 2, are vectors of observations up to time period T.

Definition 1: Independency, $x_1 \wedge x_2$:

x_1 and x_2 are independent if

$$Var\left(x_{1(T+1)}\middle|\underset{\sim}{x_1}\right)=Var\left(x_{1(T+1)}\middle|\underset{\sim}{x_1},\underset{\sim}{x_2}\right)=$$

$$=Var\left(x_{1(T+1)}\middle|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_{2(T+)}}\right) \tag{1}$$

and

$$Var\left(x_{2(T+1)}\middle|\underset{\sim}{x_2}\right)=Var\left(x_{2(T+1)}\middle|\underset{\sim}{x_1},\underset{\sim}{x_2}\right)=$$

$$=Var\left(x_{2(T+1)}\middle|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_{1(T+1)}}\right). \tag{2}$$

Definition 2: Contemporaneous relationship, $x_1 <- x_2$:

x_1 and x_2 are contemporaneously related if

$$Var(x_{1(T+1)}|\underset{\sim}{x_1})=Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}), \tag{3}$$

$$Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2})>Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_{2(T+1)}}) \tag{4}$$

and

$$Var(x_{2(T+1)}|\underset{\sim}{x_2})=Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}), \tag{5}$$

$$Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2})>Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_{1(T+1)}}). \tag{6}$$

Definition 3: Unidirectional relationship, $x_1 => x_2$:

There is a unidirectional relationship from x_1 to x_2 if

$$Var(x_{1(T+1)}|\underset{\sim}{x_1})=Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}) \tag{7}$$

and

$$Var(x_{2(T+1)}|\underset{\sim}{x_2})>Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}). \tag{8}$$

Definition 4: Feedback relationship, $x_1 <=> x_2$:

There is a feedback relationship between x_1 and x_2 if

$$Var(x_{1(T+1)}|\underset{\sim}{x_1})>Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}) \tag{9}$$

and

$$Var(x_{2(T+1)}|\underset{\sim}{x_2})>Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2}). \tag{10}$$

The above relational definitions may be generalized for the relationship between two variables, x_1 and x_2, conditional on the information of x_3. For example, the conditional feedback relationship between x_1 and x_2 given the information of x_3 is equivalent to

$$Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_3})>Var(x_{1(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_3}) \tag{11}$$

and

$$Var(x_{2(T+1)}|\underset{\sim}{x_2},\underset{\sim}{x_3})>Var(x_{2(T+1)}|\underset{\sim}{x_1},\underset{\sim}{x_2},\underset{\sim}{x_3}). \tag{12}$$

To explore the dynamic relationship of a bi-variate system, we form the five statistical hypotheses in Table 2, where the necessary and sufficient conditions corresponding to each hypothesis are given in terms of constraints on the parameter values of the VAR model.

To determine a specific causal relationship, we use a systematic multiple hypotheses testing method. Unlike the traditional pair-wise hypothesis testing, this testing method avoids the potential bias induced by restricting the causal relationship to a single alternative hypothesis. To implement this method, we employ results of several pair-wise hypothesis tests. For instance, in order to conclude that $x_1 => x_2$, we need to establish that $x_1 <\neq x_2$ and to reject that $x_1 \neq> x_2$. To conclude that $x_1 <-> x_2$, we need to establish that $x_1 <\neq x_2$ as well as $x_1 \neq> x_2$ and also to reject $x_1 \wedge x_2$. In other words, it is necessary to examine all five hypotheses in a systematic way before we draw a conclusion of dynamic relationship. The following presents an inference procedure that starts from a pair of the most general alternative hypotheses.

Table 2. Hypotheses on the dynamic relationship of a bivariate system

Hypotheses	The VAR test
H_1: $x_1 \wedge x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
H_2: $x_1 < - > x_2$	$\varphi_{12}(L) = \varphi_{21}(L) = 0$
H_3: $x_1 \not=> x_2$	$\varphi_{21}(L) = 0$
H_3^*: $x_2 \not=> x_1$	$\varphi_{12}(L) = 0$
H_4: $x_1 <=> x_2$	$\varphi_{12}(L) * \varphi_{21}(L) \neq 0$
H_5: $x_1 \not=> > x_2$	$\varphi_{21}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
H_6: $x_2 \not=> > x_1$	$\varphi_{12}(L) = 0$, and $\sigma_{12} = \sigma_{21} = 0$
H_7: $x_1 < <=> > x_2$	$\varphi_{12}(L) * \varphi_{21}(L) \neq 0$, and $\sigma_{12} = \sigma_{21} = 0$

Notes: The bivariate VAR model: $\begin{bmatrix} \varphi_{11}(L) & \varphi_{12}(L) \\ \varphi_{21}(L) & \varphi_{22}(L) \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ where x_{1t} and x_{2t} are mean adjusted variables. The first and second moments of the error structure, $\underset{\sim}{\varepsilon_t} = (\varepsilon_{1t}, \varepsilon_{2t})$, are that $E\left(\underset{\sim}{\varepsilon_t}\right) = 0$, and $E\left(\underset{\sim}{\varepsilon_t}\, \underset{\sim}{\varepsilon_{t+k}}\right) = 0$ for $k \neq 0$ and $E\left(\underset{\sim}{\varepsilon_t}\, \underset{\sim}{\varepsilon_{t+k}}\right) = \Sigma$ for $k=0$, where $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$.

Our inference procedure for exploring dynamic relationship is based on the principle that a hypothesis should not be rejected unless there is sufficient evidence against it. In the causality literature, most tests intend to discriminate between independency and an alternative hypothesis. The primary purpose of the literature cited above is to reject the independency hypothesis. On the contrary, we intend to identify the nature of the relationship between two financial series. The procedure consists of four testing sequences, which implement a total of six tests (denoted as (a) to (f)), where each test examines a pair of hypotheses. The four testing sequences and six tests are summarized in a decision-tree flow chart in Figure 1.

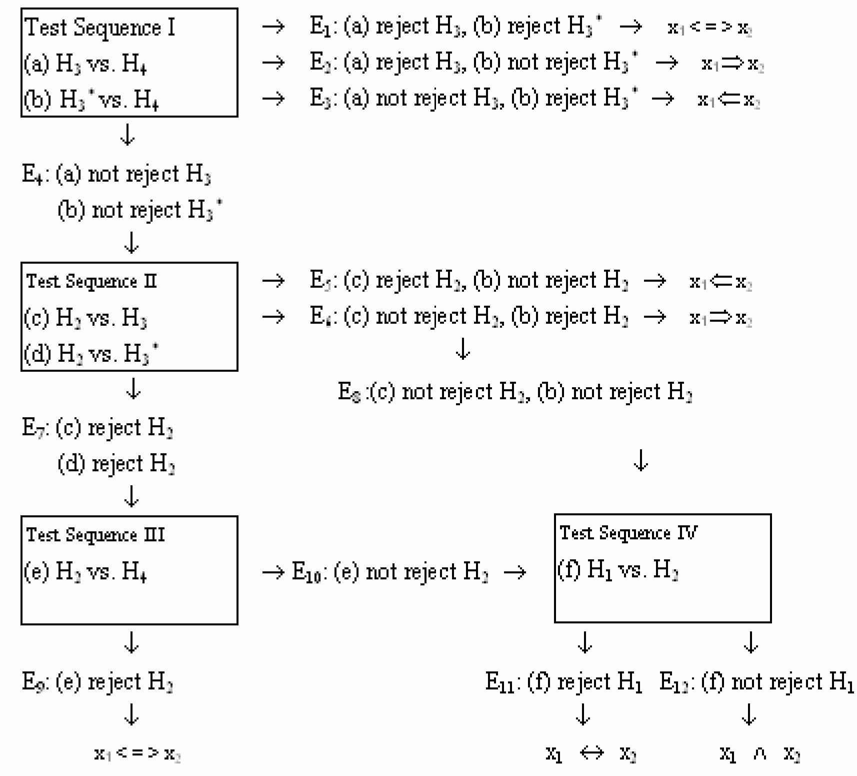

Fig. 1. Test flow chart of a multiple hypothesis testing procedure

2. Empirical results

In Tables 3-5, Panels A, B, C and D present the results using unconditional OISHA, conditional OISHA, unconditional VOLSHA and conditional VOLSHA, respectively. Table 3 presents the results of tests of hypotheses on the dynamic relationship in Table 2. In Panel A, we show that a unidirectional relationship from returns to order imbalances is 18.00% of the sample firms, while a unidirectional relationship from order imbalances to returns is 8.00%. The percentage of firms that fall into the independent category is relatively small (4.00%). Moreover, 68.00% of firms exhibit a contemporaneous relationship between returns and order imbalances. Finally, 2.00% of firms show a feedback relationship between returns and order imbalances. The percentage of firms reflecting a unidirectional relationship from returns to order imbalances is about twice as large as that from order imbalances to returns. It suggests that order imbalance is not always a good return predictor although many researches document that future daily returns could be predicted by daily order imbalances (Brown et al., 1997; Chordia & Subrahmanyam, 2004). In addition, the percentage of firms exhibiting a contemporaneous relationship is almost over sixty percent than feedback. It indicates that the interaction between returns and order imbalances on the current period is much stronger than lag periods.

Table 3. Dynamic causality relation between returns and order imbalances

	$x_1 \wedge x_2$	$x_1 < - > x_2$	$x_1 \Rightarrow x_2$	$X_1 \Leftarrow x_2$	$x_1 <=> x_2$
			$(\sigma_{12}=\sigma_{21}=0)$		
Panel A. Unconditional OISHA					
Return (x_1) and order imbalance (x_2)	4.00	68.00	18.00 (2.00)	8.00 (0.00)	2.00 (0.00)
Panel B. Conditional OISHA					
Return (x_1) and trading volume (x_2)	2.00	68.00	24.00 (2.00)	4.00 (0.00)	2.00 (2.00)
Panel C. Unconditional VOLSHA					
Return (x_1) and trading volume (x_2)	26.00	36.00	20.00 (6.00)	16.00 (8.00)	2.00 (0.00)
Panel D. Conditional VOLSHA					
Return (x_1) and trading volume (x_2)	18.00	44.00	30.00 (6.00)	6.00 (0.00)	2.00 (2.00)
Panel E. Unconditional OISHA in different time regimes					
Period 1	8.33	50.0	16.67	16.67	8.33
Period 2	0.00	58.33	8.33	33.33	0.00
Period 3	0.00	33.33	33.33	8.33	25.00
Panel F. Unconditional VOLSHA in different time regimes					
Period 1	33.33	16.67	8.33	16.67	25.00
Period 2	16.67	25.00	0.00	41.67	16.67
Period 3	16.67	16.67	33.33	16.67	16.67

Note: The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

Since the preceding tests suggest an affinitive relationship between returns and order imbalances, we proceed to identify the dynamic relationship between returns and order imbalances conditional on the information of past order imbalances[1]. The results in Panel B are similar to those in Panel A. Nevertheless, when we use trading volume instead of order imbalance, the results change significantly. Compared with the results in Panels A and B, the percentage of firms that fall into the independent category is much higher while a contemporaneous relationship is much lower in Panels C and D. It indicates that the relation between order imbalance and return is closer than that between trading volume and return. It implies that order imbalance conveys much more information than trading volume does. Moreover, the percentage of firms with a unidirectional relationship from returns to trading volume is still higher than that from trading volume to returns in Panels C and D. Panels E and F present the empirical results of the intraday relationship between returns and order imbalances in different time regimes. Panel E shows that the percentage of firms exhibiting a unidirectional relationship from order imbalance to return is 16.67, 33.33 and 8.33 in periods 1, 2 and 3, respectively. It implies that order imbalance-based trading strategies are useful from 11:30 A.M. to 2 P.M. than in other time regimes. Our empirical results are consistent with previous studies that informed trading take place from 11:30 A.M. to 2 P.M. Panel F presents that the percentage of firms exhibiting a unidirectional relationship from trading volume to return is 16.67, 41.67 and 16.67 in periods 1, 2 and 3, respectively, which implies that volume-based trading strategies are still useful from 11:30 A.M. to 2 P.M. than in other time regimes.

[1] The tests of conditional dynamic relations are based on the definitions defined in (11) and (12). The conditional tests incorporate past order imbalances into the VAR system of order imbalances and returns and therefore, account for the information impounded in past order imbalances. Furthermore, the conditional tests allow us to better identify the dynamic relationship between returns and order imbalances in an intertemporal setting.

In order to provide the evidence showing the impact of the above three variables on the relation between returns and order imbalances, in Tables 4 and 5, we divide firms into three groups according to their size and average daily trading volume of past three months and then test the multiple hypotheses of the relationship between returns and order imbalances. The results in Panel A of Table 4 indicate that the unidirectional relationship from order imbalances to returns is 11.77% in the small firm size quartile, while the corresponding number is still 11.77% in the large firm size quartile during the entire sample period. The trend is unclear.

Table 5 shows the impact of average daily trading volume of past three months on the relation between returns and order imbalances. Panel A presents that the percentage of firms exhibiting a unidirectional relationship from order imbalances to returns in small trading volume quartile is 11.76%, while that in large trading volume quartile is 5.88%. It indicates order imbalance is a better return predictor in small trading volume quartile.

Table 4. Dynamic conditional and unconditional causality relation between return and order imbalance on firm size

	$x_1 \wedge x_2$	$x_1 < - > x_2$	$x_1 \Longrightarrow x_2$	$X_1 \Longleftarrow x_2$	$x_1 <=> x_2$
Panel A. Unconditional OISHA					
Small size	5.88	58.82	17.65	11.77	5.88
Medium size	0.00	87.50	12.50	0.00	0.00
Large size	5.88	58.82	23.53	11.77	0.00
Panel B. Conditional OISHA					
Small size	5.88	75.59	17.65	5.88	5.88
Medium size	0.00	62.50	31.25	6.25	0.00
Large size	0.00	70.59	23.53	0.00	5.88
Panel C. Unconditional VOLSHA					
Small size	17.65	35.29	29.41	11.77	5.88
Medium size	18.75	62.50	18.75	0.00	0.00
Large size	17.65	35.30	41.17	5.88	0.00
Panel D. Conditional VOLSHA					
Small size	29.41	41.18	17.65	5.88	5.88
Medium size	25.00	43.75	12.50	18.75	0.00
Large size	23.53	29.41	23.53	23.53	0.00

Note: The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

Table 5. Dynamic conditional and unconditional causality relation between return and order imbalance on average daily trading volume of past three months

	$x_1 \wedge x_2$	$x_1 < - > x_2$	$x_1 \Longrightarrow x_2$	$X_1 \Longleftarrow x_2$	$x_1 <=> x_2$
Panel A. Unconditional OISHA					
Small volume	0.00	70.59	17.65	11.76	0.00
Medium volume	6.25	62.5	18.75	6.25	6.25
Large volume	5.88	70.59	17.65	5.88	0.00
Panel B. Conditional OISHA					
Small volume	5.88	58.82	23.53	11.77	0.00
Medium volume	0.00	75.00	25.00	0.00	0.00
Large volume	0.00	70.59	23.53	0.00	0.00
Panel C. Unconditional VOLSHA					
Small volume	11.77	52.94	35.29	8.70	0.00
Medium volume	18.75	50.00	18.75	12.50	0.00
Large volume	23.53	29.41	35.29	5.88	5.88

Table 5 (cont.). Dynamic conditional and unconditional causality relation between return and order imbalance on average daily trading volume of past three months

	$x_1 \wedge x_2$	$x_1 <\ -\ > x_2$	$x_1 \Rightarrow x_2$	$X_1 \Leftarrow x_2$	$x_1 <=> x_2$
Panel D. Conditional VOLSHA					
Small volume	29.41	35.30	23.53	5.88	5.88
Medium volume	25.00	43.75	12.50	18.75	0.00
Large volume	23.53	29.41	23.53	23.53	0.00

Note: The percentage of firms explained by each dynamic relationship is based on a 5% significance level of tests.

Conclusion

This study explores dynamic causality relation between return and order imbalance on extraordinary events. The conclusion is as follows. The volume-stratified results suggest that order imbalance be a return predictor in small trading volume quartile. The order imbalance-based trading strategies are useful from 11:30 A.M. to 2 P.M. than other time regimes during the event day, which is also consistent with previous finding that informed trading takes place from 11:30 A.M. to 2 P.M.

There are a few directions for further work. The bid-ask spread could be used as a proxy of information asymmetry (Llorente, Michaely, Sarr, & Wang, 2002). Barclay and Warner (1993) find although the majority of trades are small, most of the cumulative stock price change is due to medium size trades. Therefore, if we focus on medium size trades, the above effects would be powerful.

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